Generative Framework Approach to Match Landsat and Sentinel-2 Data

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Introduction: Linear regression and histogram matching based techniques have been widely used to minimize the surface reflectance difference between two similar satellite observations such as Landsat-8/9 and Sentinel-2A/B products [1]. However, regionally or globally derived conversion factors may not be suitable for all land cover types and locations, resulting in noticeable residual differences between the sensors. Generative Adversarial Network (GAN) has shown promise in the field of image processing for domain or style transfer[2]. In this work we aim to minimize the surface reflectance difference between Landsat and Sentinel-2 products based on GAN.

Material & Methods: This work selected 26 pairs of same-day Landsat and Sentinel-2 30 m spatial resolution surface reflectance images from NASA's Harmonized Landsat/Sentinel-2 project (HLS) of green band, with each pair having over 90% spatial overlap. Upstream pre-processing steps included atmospheric correction, cloud masking and BRDF normalisation. The co-registered HLS L30 and HLS S30 images of 3660×3660 pixels were divided into non-replicating 128×128 image windows. All cloud/snow/water pixels were discarded from the samples of 128×128 pixels. This resulted in a total of 1562 pairs of training samples. Out of 1562 samples, 150 were kept for test and the remaining were used in training. We treated S30 images as input data to the model and L30 images as the "ground truth" and used GAN to generate surface reflectance images based on the two inputs. GAN is a deep learning model which consists of *generator* and *discriminator* [3]. The generator tries to creates images based on random Gaussian noise input and the discriminator tries to distinguish between ground truth images or images from the generator. The adversarial training between the generator and the discriminator is carried out alternatively to minimize the classification error of the discriminator. The generator architecture was based on U-Net [2] and discriminator as PatchGAN [4] . Finally, the Landsat images generated from the Sentinel-2 images by GAN are compared to the original Landsat 8/9 images based on SSIM and MSE metrics.

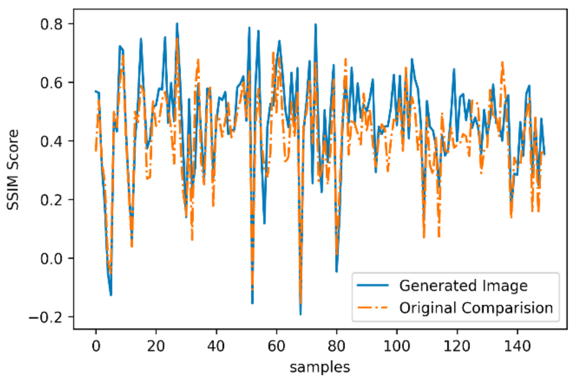

Figure 1: SSIM score comparison on original Sentinel - Landsat image and generated Sentinel - Landsat image.

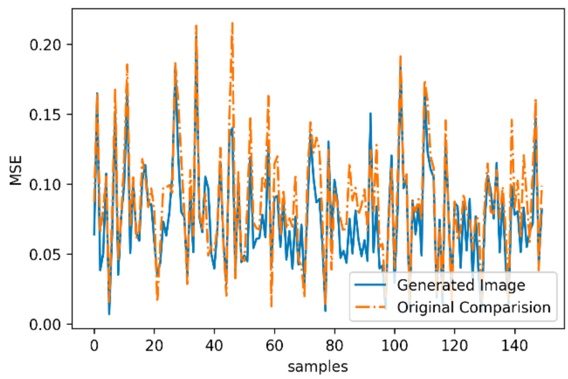

Figure 2: Mean Squared error comparison on original Sentinel - Landsat image and generated Sentinel - Landsat image

Results: GAN was trained for 45000 iterations. Once the generator was trained, we gave generator the Sentinel image tiles and correspondingly generated Landsat images. Figure 1 shows the Structural similarity score (SSIM) calculated on the test data between original L30 and S30 vs generated S30 and L30 samples. X-axis refers to the IDs of test samples (i.e. 150 of them). Figure 2 shows the mean squared error between the original L30 and S30 vs generated S30 and L30 pixel values on the scale of -1 to 1. A higher SSIM and a lower MSE indicates that two image are closer. Figure 1 clearly shows the higher SSIM score for the generated data, which can be interpreted to mean that the generated images were closer to the real Landsat images. Similarly, overall MSE for generated data was lower than the sentinel original tiles.

Significance: This study, for the first time, reports a GAN based spatial matching between Landsat and Sentinel-2 surface reflectance images. The results indicate that this approach has the potential to map data between the two satellite images with reasonable accuracy. The method can be further extended with more data and in other spectral bands and potentially be used in HLS processing. This method may be more robust and could be applied globally, potentially replacing the previous approach of simulated data. localised regression on simulated data.

References:

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